Implement K-Means clustering/ hierarchical clustering on sales_data_sample.csv dataset. Determine thenumber of clusters using the elbow method.

In [1]:
```
import pandas as pd
import numpy as np
```

In [2]:
```
df = pd.read_csv('7458_sales_data_sample.csv', encoding='unicode_escape')
```

In [3]:
```
df.head
```

Out[3]:
```
<bound method NDFrame.head of       ORDERNUMBER  QUANTITYORDERED  PRICEEACH  ORDER
LINENUMBER    SALES  \
0           10107               30      95.70                2  2871.00
1           10121               34      81.35                5  2765.90
2           10134               41      94.74                2  3884.34
3           10145               45      83.26                6  3746.70
4           10159               49     100.00               14  5205.27
...           ...              ...        ...              ...      ...
2818        10350               20     100.00               15  2244.40
2819        10373               29     100.00                1  3978.51
2820        10386               43     100.00                4  5417.57
2821        10397               34      62.24                1  2116.16
2822        10414               47      65.52                9  3079.44

            ORDERDATE    STATUS  QTR_ID  MONTH_ID  YEAR_ID  ...  \
0      2/24/2003 0:00   Shipped       1         2     2003  ...
1       5/7/2003 0:00   Shipped       2         5     2003  ...
2       7/1/2003 0:00   Shipped       3         7     2003  ...
3      8/25/2003 0:00   Shipped       3         8     2003  ...
4     10/10/2003 0:00   Shipped       4        10     2003  ...
...               ...       ...     ...       ...      ...  ...
2818   12/2/2004 0:00   Shipped       4        12     2004  ...
2819   1/31/2005 0:00   Shipped       1         1     2005  ...
2820    3/1/2005 0:00  Resolved       1         3     2005  ...
2821   3/28/2005 0:00   Shipped       1         3     2005  ...
2822    5/6/2005 0:00   On Hold       2         5     2005  ...

                       ADDRESSLINE1  ADDRESSLINE2           CITY STATE  \
0           897 Long Airport Avenue           NaN            NYC    NY
1                59 rue de l'Abbaye           NaN          Reims   NaN
2     27 rue du Colonel Pierre Avia           NaN          Paris   NaN
3                78934 Hillside Dr.           NaN       Pasadena    CA
4                   7734 Strong St.           NaN  San Francisco    CA
...                             ...           ...            ...   ...
2818             C/ Moralzarzal, 86           NaN         Madrid   NaN
2819                    Torikatu 38           NaN           Oulu   NaN
2820             C/ Moralzarzal, 86           NaN         Madrid   NaN
2821           1 rue Alsace-Lorraine          NaN       Toulouse   NaN
2822              8616 Spinnaker Dr.          NaN         Boston    MA

     POSTALCODE  COUNTRY TERRITORY CONTACTLASTNAME CONTACTFIRSTNAME DEALSIZE
0         10022      USA       NaN              Yu             Kwai    Small
1         51100   France      EMEA         Henriot             Paul    Small
2         75508   France      EMEA        Da Cunha           Daniel   Medium
3         90003      USA       NaN           Young            Julie   Medium
4           NaN      USA       NaN           Brown            Julie   Medium
...         ...      ...       ...             ...              ...      ...
2818      28034    Spain      EMEA          Freyre            Diego    Small
2819      90110  Finland      EMEA       Koskitalo           Pirkko   Medium
2820      28034    Spain      EMEA          Freyre            Diego   Medium
2821      31000   France      EMEA          Roulet          Annette    Small
2822      51003      USA       NaN         Yoshido             Juri   Medium

[2823 rows x 25 columns]>
```

In [4]:
```
df.info
```

Out[4]:
```
<bound method DataFrame.info of       ORDERNUMBER  QUANTITYORDERED  PRICEEACH  ORDERLINENUMBER    SALES  \
0           10107               30      95.70                2  2871.00
1           10121               34      81.35                5  2765.90
2           10134               41      94.74                2  3884.34
3           10145               45      83.26                6  3746.70
4           10159               49     100.00               14  5205.27
...           ...              ...        ...              ...      ...
2818        10350               20     100.00               15  2244.40
2819        10373               29     100.00                1  3978.51
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            ORDERDATE    STATUS  QTR_ID  MONTH_ID  YEAR_ID  ...  \
0      2/24/2003 0:00   Shipped       1         2     2003  ...
1       5/7/2003 0:00   Shipped       2         5     2003  ...
2       7/1/2003 0:00   Shipped       3         7     2003  ...
3      8/25/2003 0:00   Shipped       3         8     2003  ...
4     10/10/2003 0:00   Shipped       4        10     2003  ...
...               ...       ...     ...       ...      ...  ...
2818   12/2/2004 0:00   Shipped       4        12     2004  ...
2819   1/31/2005 0:00   Shipped       1         1     2005  ...
2820    3/1/2005 0:00  Resolved       1         3     2005  ...
2821   3/28/2005 0:00   Shipped       1         3     2005  ...
2822    5/6/2005 0:00   On Hold       2         5     2005  ...

                       ADDRESSLINE1  ADDRESSLINE2           CITY STATE  \
0           897 Long Airport Avenue           NaN            NYC    NY
1                59 rue de l'Abbaye           NaN          Reims   NaN
2     27 rue du Colonel Pierre Avia           NaN          Paris   NaN
3                78934 Hillside Dr.           NaN       Pasadena    CA
4                   7734 Strong St.           NaN  San Francisco    CA
...                             ...           ...            ...   ...
2818             C/ Moralzarzal, 86           NaN         Madrid   NaN
2819                    Torikatu 38           NaN           Oulu   NaN
2820             C/ Moralzarzal, 86           NaN         Madrid   NaN
2821           1 rue Alsace-Lorraine           NaN       Toulouse   NaN
2822             8616 Spinnaker Dr.           NaN         Boston    MA

     POSTALCODE  COUNTRY TERRITORY CONTACTLASTNAME CONTACTFIRSTNAME DEALSIZE
0         10022      USA       NaN              Yu             Kwai    Small
1         51100   France      EMEA         Henriot             Paul    Small
2         75508   France      EMEA        Da Cunha           Daniel   Medium
3         90003      USA       NaN           Young            Julie   Medium
4           NaN      USA       NaN           Brown            Julie   Medium
...         ...      ...       ...             ...              ...      ...
2818      28034    Spain      EMEA          Freyre            Diego    Small
2819      90110  Finland      EMEA      Koskitalo           Pirkko   Medium
2820      28034    Spain      EMEA          Freyre            Diego   Medium
2821      31000   France      EMEA          Roulet          Annette    Small
2822      51003      USA       NaN         Yoshido             Juri   Medium

[2823 rows x 25 columns]>
```

In [5]:
```
#Columns to Remove
to_drop = ['ADDRESSLINE1', 'ADDRESSLINE2', 'STATE', 'POSTALCODE', 'PHONE']
df = df.drop(to_drop, axis=1)
```

In [6]:
```
#Check for null values
df.isnull().sum()
```

Out[6]:
```
ORDERNUMBER            0
QUANTITYORDERED        0
PRICEEACH              0
ORDERLINENUMBER        0
SALES                  0
ORDERDATE              0
STATUS                 0
QTR_ID                 0
MONTH_ID               0
YEAR_ID                0
PRODUCTLINE            0
MSRP                   0
PRODUCTCODE            0
CUSTOMERNAME           0
CITY                   0
COUNTRY                0
TERRITORY           1074
CONTACTLASTNAME        0
CONTACTFIRSTNAME       0
DEALSIZE               0
dtype: int64
```

In [7]:
```
#Bhai bhai look at territory
#But territory does not have significant impact on analysis, let it be
```

In [8]:
```
df.dtypes
```

Out[8]:
```
ORDERNUMBER           int64
QUANTITYORDERED       int64
PRICEEACH           float64
ORDERLINENUMBER       int64
SALES               float64
ORDERDATE            object
STATUS               object
QTR_ID                int64
MONTH_ID              int64
YEAR_ID               int64
PRODUCTLINE          object
MSRP                  int64
PRODUCTCODE          object
CUSTOMERNAME         object
CITY                 object
COUNTRY              object
TERRITORY            object
CONTACTLASTNAME      object
CONTACTFIRSTNAME     object
DEALSIZE             object
dtype: object
```

In [9]:
```
#ORDERDATE Should be in date time
df['ORDERDATE'] = pd.to_datetime(df['ORDERDATE'])
```

In [10]:
```
#We need to create some features in order to create cluseters
#Recency: Number of days between customer's latest order and today's date
#Frequency : Number of purchases by the customers
#MonetaryValue : Revenue generated by the customers
import datetime as dt
snapshot_date = df['ORDERDATE'].max() + dt.timedelta(days = 1)
df_RFM = df.groupby(['CUSTOMERNAME']).agg({
    'ORDERDATE' : lambda x : (snapshot_date - x.max()).days,
    'ORDERNUMBER' : 'count',
    'SALES' : 'sum'
})

#Rename the columns
df_RFM.rename(columns = {
    'ORDERDATE' : 'Recency',
    'ORDERNUMBER' : 'Frequency',
    'SALES' : 'MonetaryValue'
}, inplace=True)
```

In [11]:
```
df_RFM.head()
```

Out[11]:

	Recency	Frequency	MonetaryValue
CUSTOMERNAME			
AV Stores, Co.	196	51	157807.81
Alpha Cognac	65	20	70488.44
Amica Models & Co.	265	26	94117.26
Anna's Decorations, Ltd	84	46	153996.13
Atelier graphique	188	7	24179.96

In [12]:
```
# Divide into segments
# We create 4 quartile ranges
df_RFM['M'] = pd.qcut(df_RFM['MonetaryValue'], q = 4, labels = range(1,5))
df_RFM['R'] = pd.qcut(df_RFM['Recency'], q = 4, labels = list(range(4,0,-1)))
df_RFM['F'] = pd.qcut(df_RFM['Frequency'], q = 4, labels = range(1,5))

df_RFM.head()
```

Out[12]:

CUSTOMERNAME	Recency	Frequency	MonetaryValue	M	R	F
AV Stores, Co.	196	51	157807.81	4	2	4
Alpha Cognac	65	20	70488.44	2	4	2
Amica Models & Co.	265	26	94117.26	3	1	2
Anna's Decorations, Ltd	84	46	153996.13	4	3	4
Atelier graphique	188	7	24179.96	1	2	1

In [13]:

```
#Create another column for RFM score
df_RFM['RFM_Score'] = df_RFM[['R', 'M', 'F']].sum(axis=1)
df_RFM.head()
```

Out[13]:

CUSTOMERNAME	Recency	Frequency	MonetaryValue	M	R	F	RFM_Score
AV Stores, Co.	196	51	157807.81	4	2	4	10
Alpha Cognac	65	20	70488.44	2	4	2	8
Amica Models & Co.	265	26	94117.26	3	1	2	6
Anna's Decorations, Ltd	84	46	153996.13	4	3	4	11
Atelier graphique	188	7	24179.96	1	2	1	4

We create levels for our Customers

RFM Score > 10 : High Value Customers

RFM Score < 10 and RFM Score >= 6 : Mid Value Customers

RFM Score < 6 : Low Value Customers

In [14]:

```
def rfm_level(df):
    if bool(df['RFM_Score'] >= 10):
        return 'High Value Customer'

    elif bool(df['RFM_Score'] < 10) and bool(df['RFM_Score'] >= 6):
        return 'Mid Value Customer'
    else:
        return 'Low Value Customer'
df_RFM['RFM_Level'] = df_RFM.apply(rfm_level, axis = 1)
df_RFM.head()
```

Out[14]:

	Recency	Frequency	MonetaryValue	M	R	F	RFM_Score	RFM_Level
CUSTOMERNAME								
AV Stores, Co.	196	51	157807.81	4	2	4	10	High Value Customer
Alpha Cognac	65	20	70488.44	2	4	2	8	Mid Value Customer
Amica Models & Co.	265	26	94117.26	3	1	2	6	Mid Value Customer
Anna's Decorations, Ltd	84	46	153996.13	4	3	4	11	High Value Customer
Atelier graphique	188	7	24179.96	1	2	1	4	Low Value Customer

In [15]:

```
# Time to perform KMeans
data = df_RFM[['Recency', 'Frequency', 'MonetaryValue']]
data.head()
```

Out[15]:

	Recency	Frequency	MonetaryValue
CUSTOMERNAME			
AV Stores, Co.	196	51	157807.81
Alpha Cognac	65	20	70488.44
Amica Models & Co.	265	26	94117.26
Anna's Decorations, Ltd	84	46	153996.13
Atelier graphique	188	7	24179.96

In [16]:

```
# Our data is skewed we must remove it by performing log transformation
data_log = np.log(data)
data_log.head()
```

Out[16]:

	Recency	Frequency	MonetaryValue
CUSTOMERNAME			
AV Stores, Co.	5.278115	3.931826	11.969133
Alpha Cognac	4.174387	2.995732	11.163204
Amica Models & Co.	5.579730	3.258097	11.452297
Anna's Decorations, Ltd	4.430817	3.828641	11.944683
Atelier graphique	5.236442	1.945910	10.093279

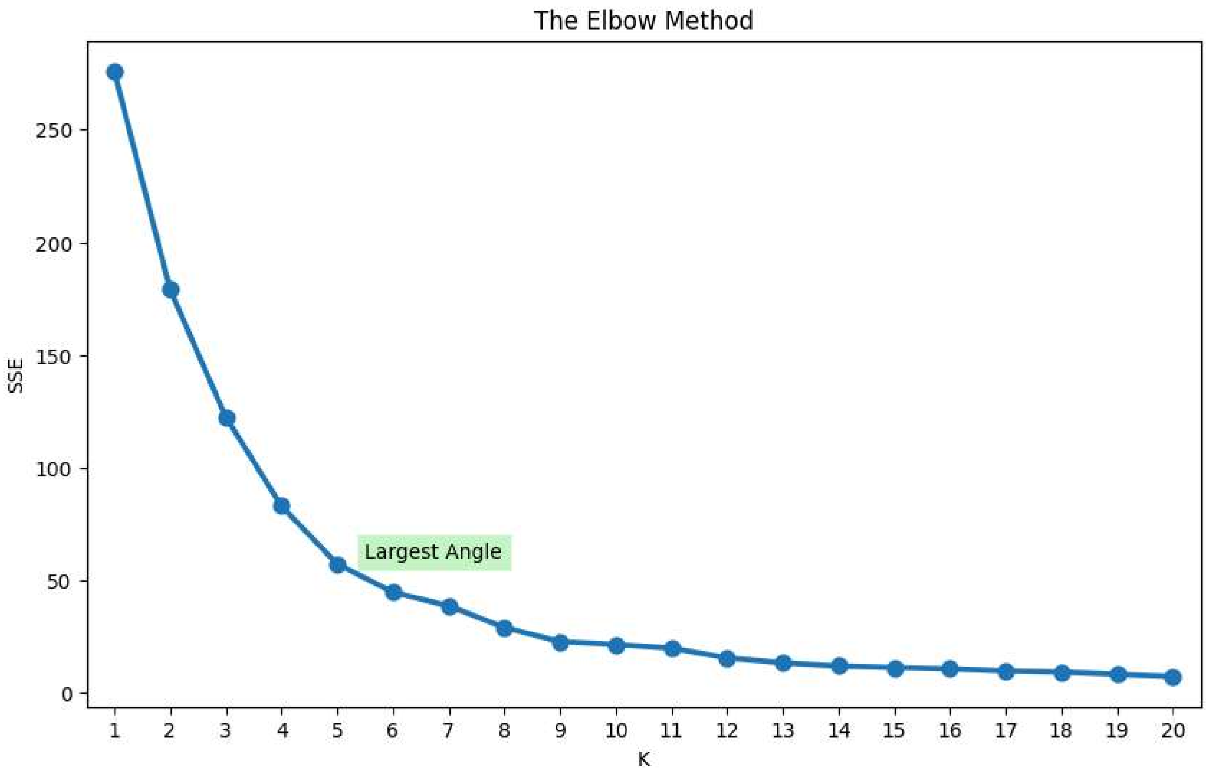
In [17]:
```
#Standardization
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(data_log)
data_normalized = scaler.transform(data_log)
data_normalized = pd.DataFrame(data_normalized, index = data_log.index, columns=dat
data_normalized.describe().round(2)
```

Out[17]:

	Recency	Frequency	MonetaryValue
count	92.00	92.00	92.00
mean	0.00	-0.00	0.00
std	1.01	1.01	1.01
min	-3.51	-3.67	-3.82
25%	-0.24	-0.41	-0.39
50%	0.37	0.06	-0.04
75%	0.53	0.45	0.52
max	1.12	4.03	3.92

In [18]:
```
#Fit KMeans and use elbow method to choose the number of clusters
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans

sse = {}

for k in range(1, 21):
    kmeans = KMeans(n_clusters = k, random_state = 1)
    kmeans.fit(data_normalized)
    sse[k] = kmeans.inertia_
```

In [19]:
```
plt.figure(figsize=(10,6))
plt.title('The Elbow Method')

plt.xlabel('K')
plt.ylabel('SSE')
plt.style.use('ggplot')

sns.pointplot(x=list(sse.keys()), y = list(sse.values()))
plt.text(4.5, 60, "Largest Angle", bbox = dict(facecolor = 'lightgreen', alpha = 0.
plt.show()
```



In [20]:

```
# 5 number of clusters seems good
kmeans = KMeans(n_clusters=5, random_state=1)
kmeans.fit(data_normalized)
cluster_labels = kmeans.labels_

data_rfm = data.assign(Cluster = cluster_labels)
data_rfm.head()
```

Out[20]:

CUSTOMERNAME	Recency	Frequency	MonetaryValue	Cluster
AV Stores, Co.	196	51	157807.81	4
Alpha Cognac	65	20	70488.44	2
Amica Models & Co.	265	26	94117.26	2
Anna's Decorations, Ltd	84	46	153996.13	4
Atelier graphique	188	7	24179.96	1